Data Mining
Classification: Alternative Techniques

Imbalanced Class Problem

Introduction to Data Mining, 2nd Edition

by

Tan, Steinbach, Karpatne, Kumar

Class Imbalance Problem

- Lots of classification problems where the classes are skewed (more records from one class than another)
  - Credit card fraud
  - Intrusion detection
  - Defective products in manufacturing assembly line

Challenges

- Evaluation measures such as accuracy is not well-suited for imbalanced class

- Detecting the rare class is like finding needle in a haystack

Confusion Matrix

- Confusion Matrix:

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a	b
	Class=No	c	d

a: TP (true positive)

b: FN (false negative)

c: FP (false positive)

d: TN (true negative)

Accuracy

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

- Most widely-used metric:

Problem with Accuracy

- Consider a 2-class problem
(total number of test samples 10.000)

  – Number of Class 0 examples = 9990
  – Number of Class 1 examples = 10

Problem with Accuracy

- Consider a 2-class problem
  - Number of Class NO examples = 990
  - Number of Class YES examples = 10
- If a model predicts everything to be class NO, accuracy is 990/1000 = 99 %
  - This is misleading because the model does not detect any class YES example
  - Detecting the rare class is usually more interesting (e.g., frauds, intrusions, defects, etc)

Alternative Measures

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a	b
	Class=No	c	d

Harmonic Mean of P and R

Alternative Measures

	PREDICTED CLASS		
		Class=Yes	Class=No
ACTUAL CLASS	Class=Yes	10	0
	Class=No	10	980

Alternative Measures

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	10	0
	Class=No	10	980

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	1	9
	Class=No	0	990

Alternative Measures

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	40	10
	Class=No	10	40

Alternative Measures

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	40	10
	Class=No	10	40

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	40	10
	Class=No	1000	4000

Measures of Classification Performance

	PREDICTED CLASS	
ACTUAL CLASS	**Yes**	**No**
Yes	TP	FN
No	FP	TN

α is the probability that we reject the null hypothesis when it is true. This is a Type I error or a false positive (FP).

β is the probability that we accept the null hypothesis when it is false. This is a Type II error or a false negative (FN).

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$$

$$ErrorRate = 1 - accuracy$$

$$Precision = Positive\ Predictive\ Value = \frac{TP}{TP + FP}$$

$$Recall = Sensitivity = TP\ Rate = \frac{TP}{TP + FN}$$

$$Specificity = TN\ Rate = \frac{TN}{TN + FP}$$

$$FP\ Rate = \alpha = \frac{FP}{TN + FP} = 1 - specificity$$

$$FN\ Rate = \beta = \frac{FN}{FN + TP} = 1 - sensitivity$$

$$Power = sensitivity = 1 - \beta$$

Alternative Measures

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	40	10
	Class=No	10	40

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	40	10
	Class=No	1000	4000

Alternative Measures

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	10	40
	Class=No	10	40

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	25	25
	Class=No	25	25

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	40	10
	Class=No	40	10

ROC (Receiver Operating Characteristic)

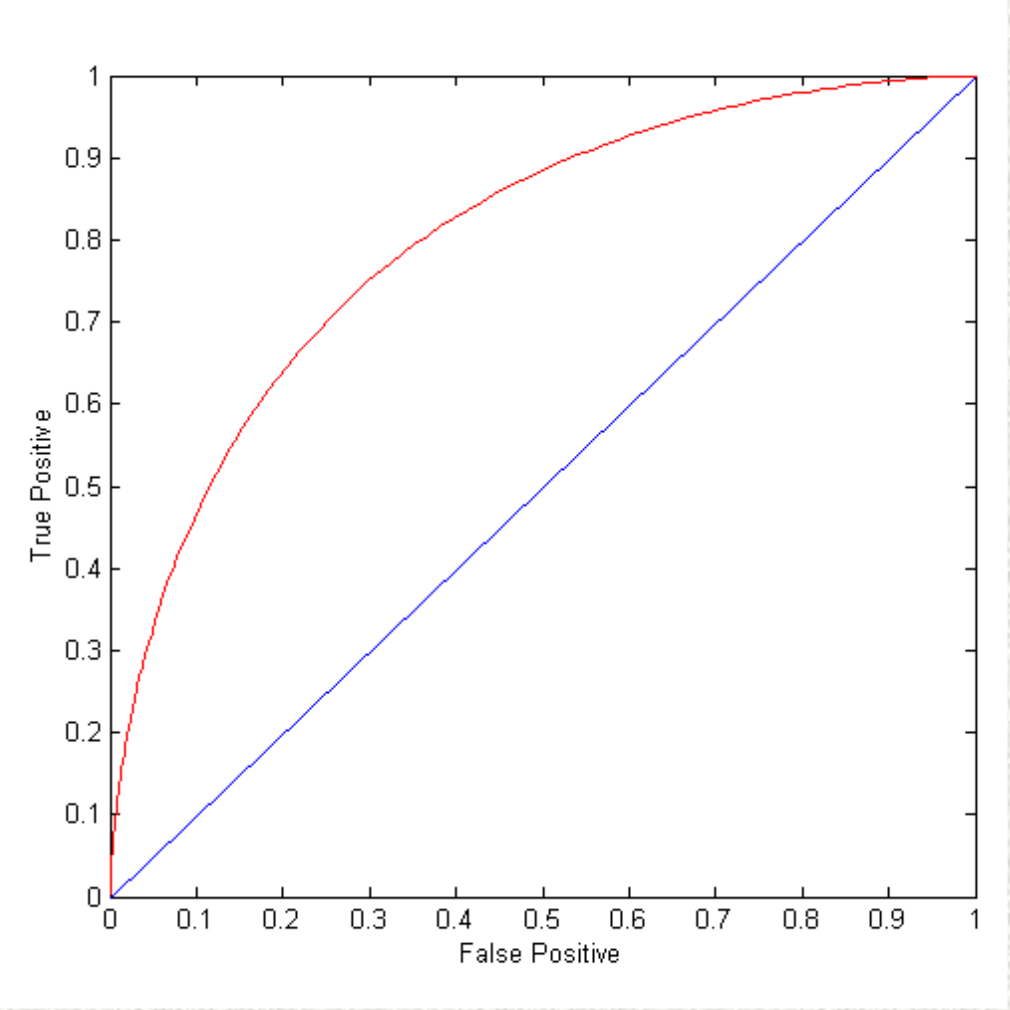
- A graphical approach for displaying trade-off between detection rate and false alarm rate
- Developed in 1950s for signal detection theory to analyze noisy signals
- ROC curve plots TPR against FPR
  - Performance of a model represented as a point in an ROC curve
  - Changing the threshold parameter of classifier changes the location of the point

ROC Curve

(TPR,FPR):

- (0,0): declare everything to be negative class
- (1,1): declare everything to be positive class
- (1,0): ideal

- Diagonal line:
  - Random guessing
  - Below diagonal line:
    - prediction is opposite of the true class



ROC (Receiver Operating Characteristic)

- To draw ROC curve, classifier must produce continuous-valued output
  - Outputs are used to rank test records, from the most likely positive class record to the least likely positive class record

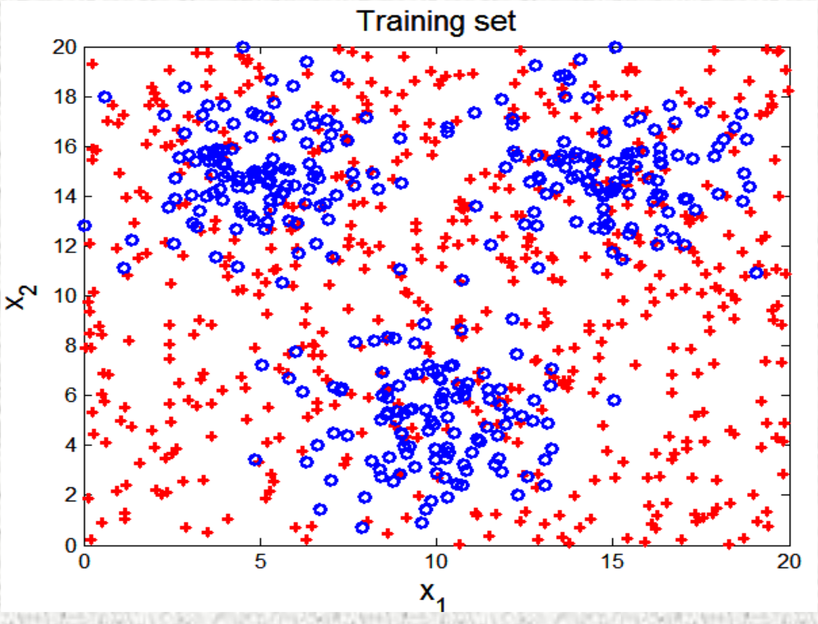
- Many classifiers produce only discrete outputs (i.e., predicted class)
  - How to get continuous-valued outputs?
    - Decision trees, rule-based classifiers, neural networks, Bayesian classifiers, k-nearest neighbors, SVM

Example: Decision Trees

Decision Tree

Continuous-valued outputs

ROC Curve Example

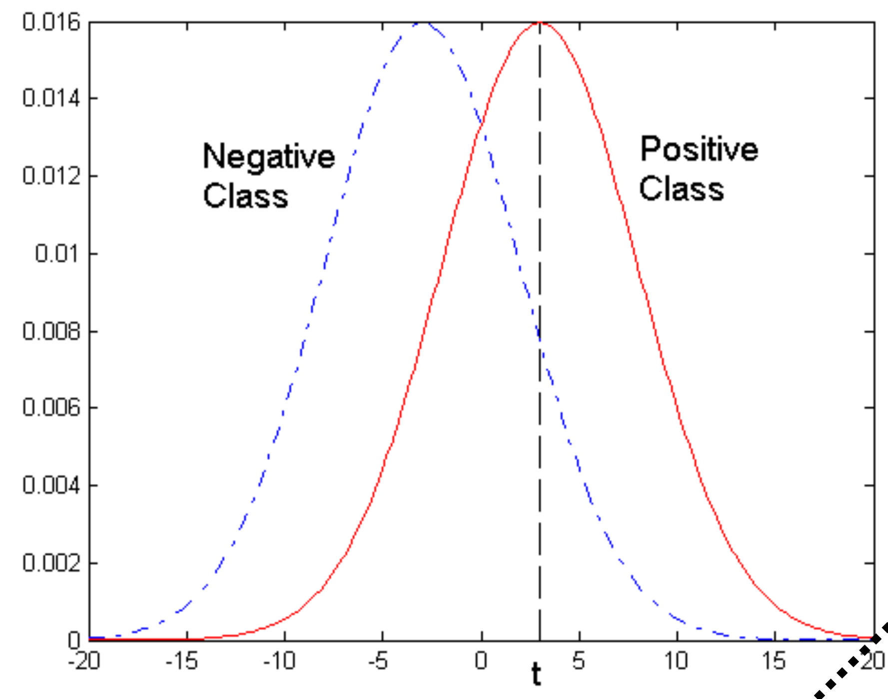


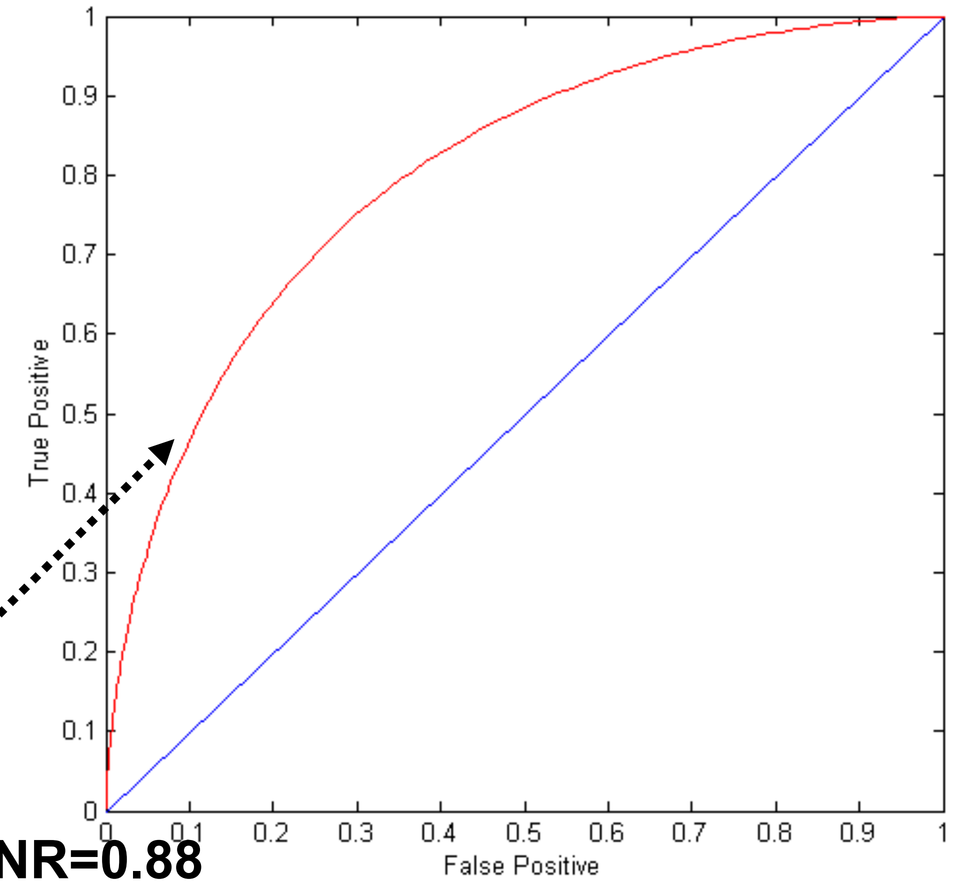
$\alpha = 0.3$		Predicted Class	
		Class o	Class +
Actual Class	Class o	645	209
	Class +	298	948

$\alpha = 0.7$		Predicted Class	
		Class o	Class +
Actual Class	Class o	181	673
	Class +	78	1168

ROC Curve Example

- 1-dimensional data set containing 2 classes (positive and negative)
- Any points located at x > t is classified as positive

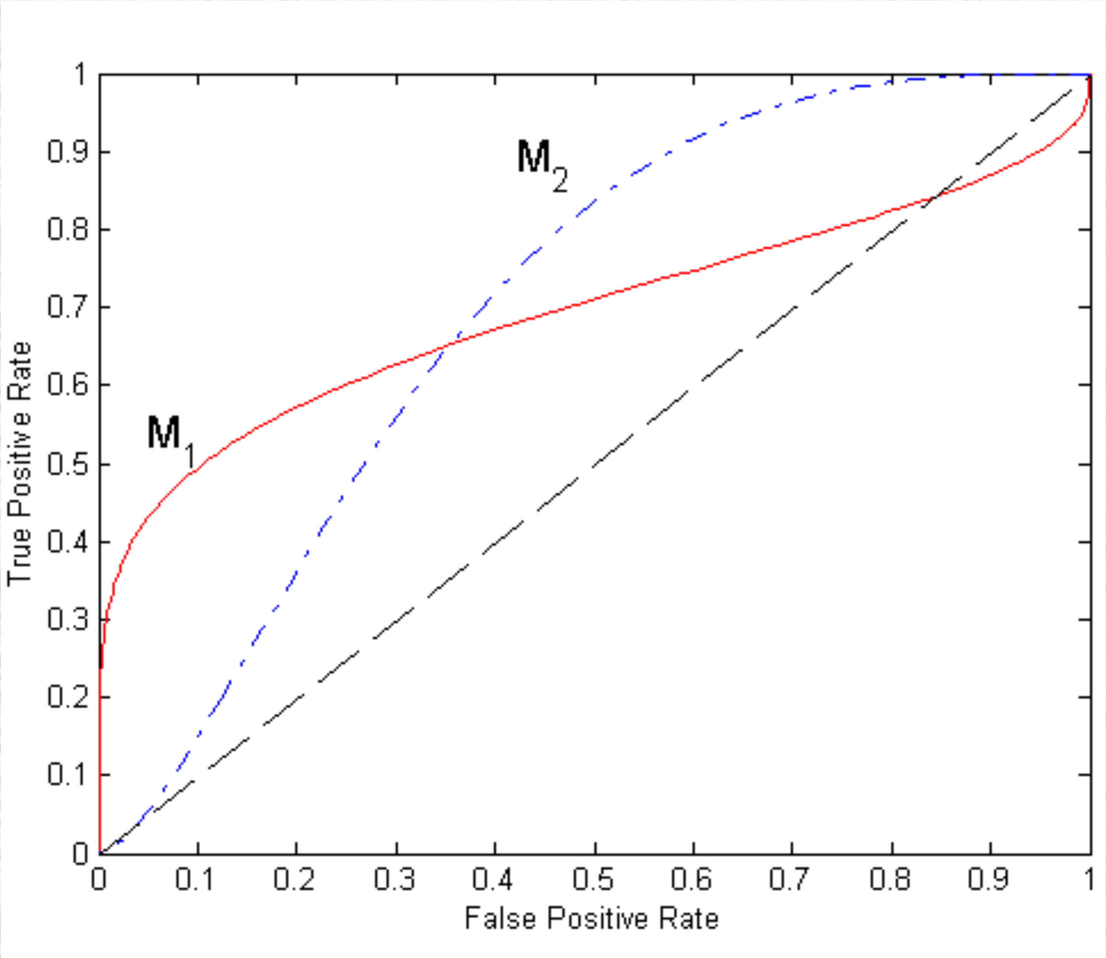




At threshold t:

TPR=0.5, FNR=0.5, FPR=0.12, TNR=0.88

Using ROC for Model Comparison



- No model consistently outperform the other
  - M_1 is better for small FPR
  - M_2 is better for large FPR
- Area Under the ROC curve
  - Ideal:
    - Area = 1
  - Random guess:
    - Area = 0.5

How to Construct an ROC curve

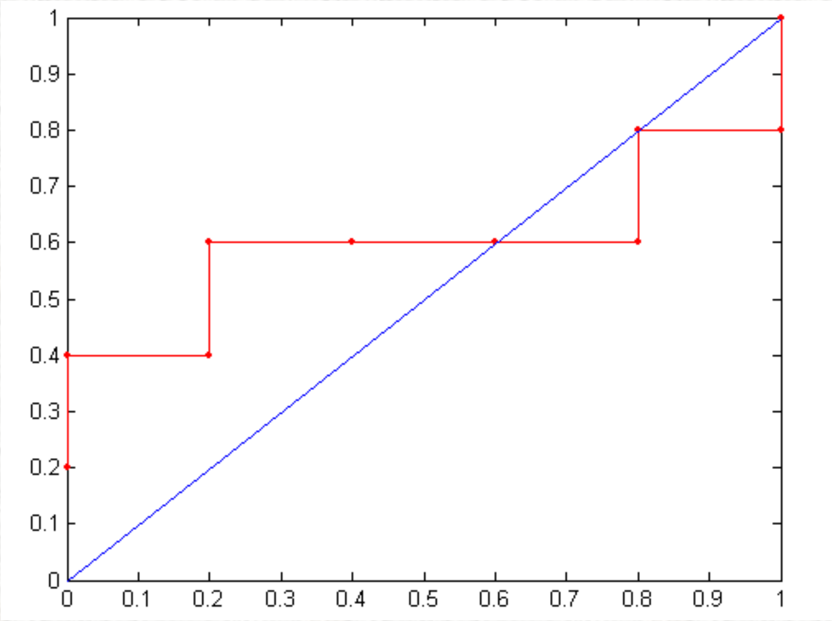
Instance	Score	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.85	-
5	0.85	-
6	0.85	+
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

- Use a classifier that produces a continuous-valued score for each instance
  - The more likely it is for the instance to be in the + class, the higher the score
- Sort the instances in decreasing order according to the score
- Apply a threshold at each unique value of the score
- Count the number of TP, FP, TN, FN at each threshold
  - TPR = TP/(TP+FN)
  - FPR = FP/(FP + TN)

How to construct an ROC curve

Threshold >=

ROC Curve:



Handling Class Imbalanced Problem

- Class-based ordering (e.g. RIPPER)
  - Rules for rare class have higher priority
- Cost-sensitive classification
  - Misclassifying rare class as majority class is more expensive than misclassifying majority as rare class
- Sampling-based approaches

Cost Matrix

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	f(Yes, Yes)	f(Yes,No)
	Class=No	f(No, Yes)	f(No, No)

C(i,j): Cost of misclassifying class i example as class j

Cost Matrix	PREDICTED CLASS		
ACTUAL CLASS	C(i, j)	Class=Yes	Class=No
	Class=Yes	C(Yes, Yes)	C(Yes, No)
	Class=No	C(No, Yes)	C(No, No)

Computing Cost of Classification

Cost Matrix	PREDICTED CLASS		
	C(i,j)	+	-
ACTUAL CLASS	+	-1	100
	-	1	0

Model M_1	PREDICTED CLASS		
		+	-
ACTUAL CLASS	+	150	40
	-	60	250

Model M_2	PREDICTED CLASS		
		+	-
ACTUAL CLASS	+	250	45
	-	5	200

Accuracy = 80%
Cost = 3910

Accuracy = 90%
Cost = 4255

Cost Sensitive Classification

- Example: Bayesian classifer
  - Given a test record x:
    - Compute p(i|x) for each class *i*
    - Decision rule: classify node as class k if
  - For 2-class, classify x as + if p(+|x) > p(-|x)
    - This decision rule implicitly assumes that
      C(+|+) = C(-|-) = 0 and C(+|-) = C(-|+)

Cost Sensitive Classification

- General decision rule:
  - Classify test record x as class k if

- 2-class:
  - Cost(+) = p(+|x) C(+,+) + p(-|x) C(-,+)
  - Cost(-) = p(+|x) C(+,-) + p(-|x) C(-,-)
  - Decision rule: classify x as + if Cost(+) < Cost(-)
    - if C(+,+) = C(-,-) = 0:

Sampling-based Approaches

- Modify the distribution of training data so that rare class is well-represented in training set
  - Undersample the majority class
  - Oversample the rare class

- Advantages and disadvantages